Reprinted from *Agronomy Journal*
Vol. 89, No. 4

An Empirical Model of Diurnal Temperature Patterns

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ABSTRACT

Air temperature is a key driving factor in many crop growth models. Hourly air temperature data required for input are often not available and must be estimated from daily extremes. Several methods to model diurnal patterns exist; all are arbitrary functions of time during the day, chosen to match the daily pattern. Of all possible mathematical shapes, it would be preferable to use the one generated by the data themselves. Thus, our objective was to develop an empirical model to reconstruct the diurnal air temperature curve from measured daily extremes. As usual, temperature was normalized to range from 0 to 1 at the daily extremes. However, we also normalized time, to reduce seasonal variation in the shape of the temperature pattern. Calibration consisted of developing the cumulative distribution function of normalized temperature for a year's data, fitting a beta distribution to the data, and evaluating the 50th percentile, all as a function of time. The resulting vectors of normalized time and air temperature were used to generate diurnal patterns from daily extremes. The model was calibrated with one year's data for each of 14 sites across the USA, and tested for additional years at each site. For the total 32 site-years, annual mean r^2 ranged from 0.47 to 0.87, with values highest for Arizona sites, intermediate for South Carolina, and lowest for mountainous Idaho sites. Model performance was better than or equal to that of the next-best model in 16 of 32 site-years, and also overall. Normalization of both time and temperature produced diurnal air temperature patterns that were sufficiently general to apply with minimal loss of predictive accuracy at widely separate sites in the USA.

Ambient air temperature is a fundamental requirement of many models of physical and biological systems, such as those describing crop phenology and development based on the seasonal accumulation of growing degree days. Usually, temperature data are input depending on the model's time step. Those with a daily time step generally utilize daily extremes or the mean daily temperature (e.g., Jones and Kiniry, 1986); models with a shorter time step require input of temperature data at subdaily intervals. Unfortunately, subdaily temperature data are not often recorded at many locations or may not be easily accessible because of the file size, making the only temperature data available the daily minima and maxima. When subdaily data are not available, the shorter time step models must employ a submodel to approximate diurnal temperatures from daily extremes.

The shape of the diurnal temperature curve has been modeled with a variety of methods with varying degrees of complexity. These methods include linear models (Sanders, 1975), simple curve-fitting models based typically on sine or Fourier analysis (Walter, 1967; Johnson and Fitzpatrick, 1977; De Wit et al., 1978; Parton and Logan, 1981; Kline et al., 1982; Acock et al., 1983; Wilkerson et al., 1983; Floyd and Braddock, 1984; Worner, 1988; Fernandez, 1992), and more complex energy budget models (Myrup, 1969; Lemon et al., 1971; Goudriaan and Waggoner, 1972).

The linear and simple curve models have an advantage in that they are easy to use and often require only daily minimum and maximum temperatures. Reicosky et al. (1989) examined the accuracy of five such existing methods, three of which are currently used in existing soybean growth models, for calculating hourly air temperature from daily extremes. All methods worked well on clear days, but had limited success on overcast days. They concluded that, when accuracy of temperature input to crop simulation models is critical, direct measurement of hourly temperature may be necessary.

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Published in Agron. J. 89:542–548 (1997).

Abbreviations and variables: ABSRES, sum of the absolute value of the residuals; CDF, cumulative distribution function; D, daylength; H_a, time of observation; H_n, normalized time of observation; H_r, time of sunrise; H_s, time of sunset; i and j (in subscripts with temperature variables), day i and time j; MSE, mean square error; RES, sum of residuals; RMSE, root mean square error; T_a, measured air temperature; T_c, calculated air temperature; T_{min} and T_{max}, minimum and maximum air temperature; T_n, normalized air temperature; Γ, gamma distribution function; α, shape parameter for the Γ-function; β, shape parameter for the Γ-function.

All such models of diurnal patterns consist of some type of curve designed to approximate a typical, clear-day temperature pattern. As such, the accuracy of the model in matching a diurnal pattern depends both on the uniformity of the daily temperature pattern and on the degree to which the theoretical pattern matches the real, typical pattern. Our objective was to develop an empirical model to describe the shape of the diurnal air temperature curve that is not restricted by the assumption that the shape of the daily pattern fits a predefined curve, such as a sine wave. The model, designated herein as TFIT, can be used in either of two modes, deterministically or stochastically. This work reports development and evaluation of the reconstruction of diurnal air temperature patterns from daily temperature extremes for the deterministic mode.

MATERIALS AND METHODS

Data Collection

The hourly air temperature data used to calibrate and test the model were obtained from 14 sites (Table 1). A total of 46 data sets were used. Temperature data from the first year at each site were used to parameterize the model. For parameterization only, days with precipitation (>0.5 mm) were omitted from the data set to avoid skewing the temperature distributions. This was done because rain exerts a predictable influence on diurnal patterns and thus can be modeled using a routine contingent on occurrence of rain, such as the wet-day vs. dry-day output of WGEN (Richardson and Wright, 1984). All other days were included irrespective of whether they contained atypical weather events, such as frontal passage. The remaining years' data at each site were used for testing. During tests, days with precipitation were included.

Model Development

The shape of the diurnal temperature cycle is closely related to the receipt of global irradiance (Campbell, 1977). Fluctuations in the shape of daily air temperature curve can be attributed to daily and annual periodicities, as well as aperiodic (irregular) fluctuations resulting from, for instance, frontal passage. Annual variation arising from phase angle changes, as a result of the progression of the earth's position relative to the sun throughout the year, tends to shift the time of minimum and, for some sites, maximum temperature to an extent dependent on daylength (Walter, 1967). Similarly, atypical weather events displace the times of the daily temperature extremes, as well as affecting the magnitude of the daily temperature range. We developed a continuous function that accounts for annual and diurnal variation by normalizing both the temperature and time scales.

Hourly air temperature data are implicitly or explicitly normalized in all models. In our work, they were explicitly normalized:

$$T_{n(ij)} = \frac{T_{a(ij)} - T_{min(i)}}{T_{max(i)} - T_{min(i)}} \qquad [1]$$

where $T_{n(ij)}$ is normalized air temperature on day i at time j, $T_{a(ij)}$ is measured air temperature on day i at time j, $T_{min(i)}$ is minimum air temperature on day i, and $T_{max(i)}$ is maximum air temperature on day i. This procedure scales the amplitude of the daily curve to account for variation in the daily temperature range. Performing this step, alone, allows a distribution of hourly air temperatures to be developed, but aggregating more than a month's data this way will include variation caused by seasonal changes in daylength. Thus, some method to account for such seasonality is required.

The first unique feature of this work is the normalization of time. To minimize annual variation, the time scale of the hourly air temperature observations (H_a) was normalized, with 0000 h, sunrise (H_r), sunset (H_s), and 2400 h defined as 0.00, 0.25, 0.75, and 1.00, respectively:

$$H_n = 0.25\frac{H_a}{H_s} \qquad 00 \le H_a < H_r$$

$$H_n = 0.50\frac{H_a - H_r}{D} + 0.25 \qquad H_r \le H_a < H_s$$

$$H_n = 0.25\frac{H_a - H_s}{24 - H_s} + 0.75 \qquad H_s \le H_a < 24 \qquad [2]$$

where H_n is normalized time and D is daylength in hours. This process fixes the time of sunrise and sunset, thus stabilizing the effect that D or position within a time zone may have on the shape of the diurnal pattern. Stabilizing the shape of the curve, normalized in both dimensions, creates a family of daily curves that can now be described stochastically, which is the second unique feature of this work.

At any given time during the day, the normalized temperature is bounded by 0 and 1. Near dawn, the distribution of values will be skewed toward 0; in early afternoon, they will be skewed near 1. Distributions bounded between 0 and 1 and that exhibit positive, negative, or no skew can be described by the beta distribution.

The normalized air temperatures were sorted into 20 classes (width = 0.05) of normalized time. A two-parameter beta distribution was fit to the cumulative distribution function

Table 1. Sites of historical, hourly weather data used to calibrate and test the TFIT model.

Location	Lat N	Long W	Elevation	Year
			m	
Aguila, AZ	33°57′	113°11′	655	1987–1988
Coolidge, AZ	32°59′	111°36′	422	1987–1988
Parker, AZ	33°53′	114°27′	94	1987–1988
Safford, AZ	32°49′	109°41′	901	1987–1988
Tucson, AZ	32°17′	110°57′	713	1987–1988
Yuma Valley, AZ	32°43′	114°42′	35	1987–1988
Boise, ID (Quonset)	43°12′	116°45′	1194	1992–1993
Reynolds Mtn., ID	43°04′	116°45′	2098	1992–1993
West Lafayette, IN	40°21′	86°52′	183	1978–1979
Morris, MN	45°35′	95°53′	348	1986–1988
Lincoln, NE	40°51′	96°45′	366	1991–1995
Pendleton, OR	45°43′	118°38′	454	1982–1988
Kutztown, PA (Rodale)	40°25′	75°56′	120	1985–1987
Florence, SC	34°08′	79°26′	41	1985–1995

(CDF) of temperatures within each of these classes. The beta density function is given by:

$$f_\beta(x) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\,\Gamma(\beta)}\, x^{\alpha-1}\,(1 - x)^{\beta-1}$$
$$\alpha > 0, \beta > 0, 0 \leq x \leq 1 \qquad [3]$$

where Γ is the gamma distribution, α and β are shape parameters, and x is the beta variable. The mean and variance of each class were used as moment estimators of α and β (Haan, 1977). The CDF of the beta distribution was obtained by numerically integrating Eq. [3]. To test the hypothesis that the beta CDF accurately fits the temperature CDF, Kolmogorov–Smirnov (K–S) goodness-of-fit tests were run for each class of a Florence, SC, test data set from 1985 to 1987. The hypothesis was rejected ($P = 0.05$) in six of the twenty classes (0.15, 0.20, 0.25, 0.55, 0.60, and 1.0) as a result of the high percentage of either 0 (the minimum) or 1 (the maximum) values occurring in the measured data, while the theoretical percentages at these points in the beta distribution are defined as zero. Because the beta CDF fit the remaining data points well, and the predictive error involved during those times was small, we decided to retain the beta distribution.

Work at our laboratory in Florence, SC, has used these stochastic descriptors in both a stochastic and deterministic mode. The remainder of this report will describe only the deterministic mode, which is the first step in implementing the procedure for use in deterministic models. Such models require air temperature as a function of time. The 50th percentile of the CDF for each of the 20 classes of normalized time resulted in a set of 20 x,y pairs. A procedure to convert normalized air temperature and time to conventional units is described below.

Deterministic Mode

Conversion of normalized air temperature is straightforward using Eq. [1] solved for T_a. However, to avoid discontinuities caused by switching from one set of daily extremes to another at midnight, the different parts of the day are calculated from different sets of minimum and maximum temperatures. Our model, TFIT, divides the day into three segments: midnight to sunrise, sunrise to sunset, and sunset to midnight. The calculated air temperatures during each segment are calculated as follow:

$$T_{c(ij)} = T_{\max(i-1)} - (1.0 - T_{n(j)})\,(T_{\max(i-1)} - T_{\min(i)}) \qquad 00 \leq H_n < H_r$$
$$T_{c(ij)} = T_{n(j)}(T_{\max(i)} - T_{\min(i)}) + T_{\min(i)} \qquad H_r \leq H_n < H_s$$
$$T_{c(ij)} = T_{\max(i)} - (1.0 - T_{n(j)})\,(T_{\max(i)} - T_{\min(i+1)}) \qquad H_s \leq H_n < 24 \qquad [4]$$

where $T_{c(ij)}$ is calculated air temperature on day i at time j, and $T_{n(j)}$ is the normalized air temperature at time j calculated from the 50th-percentile values. Similarly, normalized time is converted to standard time based on solutions of Eq. [2] for the appropriate time periods.

Model Validation

There are three aspects of model accuracy: how well the calculated values of air temperature match measured values, how well the model performs compared with alternative methods, and how widely-applicable any one set of the model's parameters might be. First is the question of how accurately the calculated temperatures matched the measurements. Evaluating models that produce time series has been the subject of much discussion. For simplicity and for familiarity, the regression coefficient, r^2, was used for the comparison of simulated and measured hourly values. However, r^2 must be interpreted carefully, because diurnal and annual variations in the time series will artifactually increase its value. To avoid the annual variation inflating r^2, daily r^2 values were computed, and monthly and annual mean r^2 values were then calculated.

Aspect number two was addressed by comparing TFIT with five existing models: SAWTOOTH (Sanders, 1975), TEMP (Parton and Logan, 1981), WAVE (De Wit et al., 1978), WCALC (Wilkerson et al., 1983), and WEATHER (Acock et al., 1983). The general assumptions of each model are summarized in Table 2, while a detailed review of the methods used in these five temperature models can be found in Reicosky et al. (1989), who previously evaluated their accuracy. The times of the extremes are either set to specific hours or are calculated as empirical functions of sunrise and sunset. All models require daily minimum and maximum air temperature as input, and some require location latitude and longitude to calculate sunrise and sunset times.

Several statistics were calculated for each day in the data set to evaluate the relative accuracy of TFIT and the other models. Each statistic was subjected to analysis of variance, and means were separated with the Waller–Duncan k-ratio t-test ($P = 0.05$) (SAS, 1990). The first of these statistics was the correlation coefficient (r) between calculated temperature (T_c) and measured temperature (T_a) for each hour of a day. The inverse hyperbolic tangent transform of r was calculated to ensure that it was approximately normally distributed, which is a requirement of the analysis of variance (Steel and Torrie, 1980). Although means separation was performed on transformed r, tables presented here will be presented as r^2 to ease interpretation.

The mean square error (MSE) was calculated to reflect the accuracy of the shape of the calculated curve to the measured curve:

$$\mathrm{MSE} = \sum_{j=1}^{24} \frac{(T_{a(j)} - T_{c(j)})^2}{n} \qquad [5]$$

where $T_{a(j)}$ is measured air temperature at time j, $T_{c(j)}$ is calculated air temperature at time j, and n is the number of observations. To satisfy the assumption of normality for the analysis of variance, the MSE rather than the root MSE (RMSE) was used because it is likely to have the chi-square distribution, which approaches a normal distributions for large degrees of

Table 2. Descriptions and assumptions of the six diurnal temperature models, including TFIT.

Model	Identifier	Time of minimum	Time of maximum	Day function	Night function
SAWTOOTH (Sanders, 1975)	SAWT	0500 h	1500 h	linear	linear
TEMP (Parton and Logan, 1981)	TEMP	empirical	empirical	sine	exponential
WAVE (De Wit et al., 1978)	WAVE	H_r†	1400 h	cosine	cosine
WCALC (Wilkerson et al., 1983)	CALC	H_r + 2 h	f(day)†	sine	linear
WEATHER (Acock et al., 1983)	WEAT	H_r	f(sol)†	sine	exponential
TFIT	TFIT	empirical	empirical	empirical	empirical

† H_r, sunrise; f(day), cosine function of daylength; f(sol), function of solar radiation.

freedom (Steel and Torrie, 1980). The MSE was logarithmically (base 10) transformed prior to analysis, which is a common procedure when performing the analysis of variance on variances. Again, interpretation of log-transformed MSE is not intuitive, so tables presented here will be RMSE, but the mean separations indicated were performed on log MSE.

The sum of the residuals (RES) and the sum of the absolute value of the residuals (ABSRES) were used to evaluate how consistent the models were in calculating air temperature throughout a daily cycle:

$$\mathrm{RES} = \sum_{j=1}^{24} (T_{a(j)} - T_{c(j)}) \qquad [6]$$

$$\mathrm{ABSRES} = \sum_{j=1}^{24} |T_{a(j)} - T_{c(j)}| \qquad [7]$$

A value of RES close to zero indicates an unbiased model, and smaller values of ABSRES indicate better performance.

To this point, all model runs were conducted using the initial year's (or season's) data at each site as calibration, and subsequent year's data for testing. The third aspect, generality, was addressed by comparing normal curves for all sites and by testing one site's parameters against another site's data.

RESULTS AND DISCUSSION

Performance of TFIT Against Measured Air Temperatures

The statistical summary of all tests against subsequent years' data is shown in Table 3. For the 32 site-years, r^2 ranged from 0.47 to 0.87. Results for the Arizona sites were the highest, with all $r^2 > 0.80$. Results for the 10 yr of South Carolina data were intermediate, ranging from 0.75 to 0.82. Results from the mountainous Idaho sites were the poorest, ranging from 0.47 to 0.59. In contrast to r^2, the RMSE values were generally lower for South Carolina than for Arizona, reflecting different distributions of deviations from measured air temperature. Summed deviations from measured air temperature were small, with one case representing more than 1°C average underestimate each hour. The average absolute errors were also small, with only two nonmountainous site-years exceeding a sum of 48, representing a 2°C average.

Comparison of TFIT with Other Models

The comparison of our model, TFIT, with the five other models is summarized in Table 4. Analysis of variance was performed on correlation coefficient, r, and mean square error, MSE, after transformation to approach normal distributions. However, both transformed variables are difficult to interpret, so the table lists r^2 and RMSE, followed by lowercase letters indicating where the transformed means are not significantly different according to the Waller–Duncan test at the 0.05 level. In addition, because the six methods are rarely sorted in the same order, the means have been arranged alphabetically by method, with the numerical best case highlighted for convenience.

Values for RMSE for all models ranged from 1.60 to 6.44°C, with those for the TFIT model ranging from 1.60 to 4.30°C. Of the 10 highest values for RMSE, 6 were the 6 yr for Pendleton, OR. The two highest values

Table 3. Summary statistics for 32 site-years of TFIT calculated air temperatures compared with measured hourly temperatures. Values are annual means of daily statistics.†

Location	Test year	Calibration year	n	r^2	RMSE	RES	ABSRES
Morris, MN	1988	1986	181	0.813	2.124	−12.782	40.203
Aguila, AZ	1988	1987	360	0.830	2.379	−0.197	42.388
Coolidge, AZ	1988	1987	363	0.841	2.394	0.751	44.279
Parker, AZ	1988	1987	363	0.838	2.229	2.601	41.214
Safford, AZ	1988	1987	363	0.866	2.305	0.405	43.251
Tucson, AZ	1988	1987	356	0.853	2.244	1.350	40.591
Yuma Valley, AZ	1988	1987	360	0.824	2.336	−2.311	43.854
Boise, ID (Quonset)	1993	1992	348	0.594	4.303	−33.499	81.106
Reynolds Mtn., ID	1993	1992	363	0.472	3.650	−18.431	71.002
Lincoln, NE	1992	1991	363	0.684	2.103	−4.485	39.644
Lincoln, NE	1993	1991	363	0.653	2.023	−4.010	38.293
Lincoln, NE	1994	1991	363	0.693	2.123	−6.634	40.391
Lincoln, NE	1995	1991	363	0.659	2.158	−2.199	40.979
Pendleton, OR	1983	1982	321	0.675	2.383	−5.399	44.668
Pendleton, OR	1984	1982	339	0.678	2.361	−3.630	43.662
Pendleton, OR	1985	1982	352	0.690	2.527	−6.236	46.341
Pendleton, OR	1986	1982	354	0.674	2.376	−1.899	44.213
Pendleton, OR	1987	1982	355	0.689	2.695	−4.967	49.477
Pendleton, OR	1988	1982	349	0.695	2.661	−4.714	49.060
Kutztown, PA	1986	1985	357	0.739	1.804	−6.786	33.641
Kutztown, PA	1988	1985	358	0.756	1.765	−4.779	33.194
W. Lafayette, IN	1979	1978	90	0.797	1.600	−2.593	29.634
Florence, SC	1986	1985	363	0.768	1.879	−4.831	34.635
Florence, SC	1987	1985	363	0.772	1.790	−4.746	33.360
Florence, SC	1988	1985	353	0.766	1.928	−6.816	35.584
Florence, SC	1989	1985	348	0.761	1.766	−3.789	32.663
Florence, SC	1990	1985	351	0.822	1.858	−2.464	34.115
Florence, SC	1991	1985	347	0.782	1.864	−6.452	34.505
Florence, SC	1992	1985	306	0.791	2.001	−3.870	36.938
Florence, SC	1993	1985	334	0.797	2.068	−5.130	38.229
Florence, SC	1994	1985	349	0.755	2.170	−3.163	40.244
Florence, SC	1995	1985	349	0.772	2.146	−0.138	39.138

† RMSE, root mean square error; RES, sum of residuals; ABSRES, sum of the absolute value of the residuals.

Table 4. Values of RMSE and r^2 with means separation on transformed parameters of six models for 32 site-years.†

		RMSE						r^2					
Location	n	CALC‡	SAWT	TEMP	TFIT	WAVE	WEAT	CALC	SAWT	TEMP	TFIT	WAVE	WEAT
Morris, MN	181	3.04a§	2.14b	3.25a	2.12b¶	2.30b	2.24b	0.68b	0.79a	0.63c	0.81a	0.78a	0.79a
Aguila, AZ	360	2.84a	2.22c	2.64a	2.38b	1.98d	2.52b	0.79d	0.86b	0.79d	0.83c	0.87a	0.84c
Coolidge, AZ	363	2.89a	2.23c	3.00a	2.39b	2.06d	2.38cb	0.80d	0.87b	0.76e	0.84c	0.88a	0.87b
Parker, AZ	363	2.58b	2.11dc	2.84a	2.23c	2.06d	1.91e	0.80d	0.86c	0.76e	0.84c	0.86b	0.88a
Safford, AZ	363	2.85a	2.35b	2.67a	2.31b	2.34b	2.70a	0.81d	0.85b	0.81d	0.87a	0.85ba	0.83c
Tucson, AZ	356	2.72a	2.16c	2.67a	2.24c	2.00d	2.48b	0.80d	0.86b	0.78d	0.85b	0.86a	0.84c
Yuma Valley, AZ	360	2.76a	1.96d	2.84a	2.34b	1.85e	2.27c	0.78e	0.88b	0.74f	0.82d	0.87a	0.85c
AZ mean	2 165	2.77a	2.17c	2.78a	2.31b	2.05d	2.38b	0.80e	0.86b	0.77f	0.84d	0.87a	0.85c
Boise, ID (Quonset)	348	4.58bc	3.77d	3.70d	4.30b	4.13c	6.44a	0.59c	0.61abc	0.63a	0.59bc	0.61ab	0.29d
Reynolds Mtn., ID	363	3.43cd	3.21d	3.17cd	3.65b	3.54c	4.66a	0.52a	0.51a	0.51a	0.47b	0.50a	0.32c
Lincoln, NE	363	2.29b	1.82d	2.47a	2.10c	1.99cd	2.01c	0.64c	0.72a	0.58d	0.68b	0.70ab	0.69ab
Lincoln, NE	363	2.14b	1.74d	2.39a	2.02bc	1.95c	2.04bc	0.64c	0.70a	0.54d	0.65b	0.68ab	0.64b
Lincoln, NE	363	2.37b	1.80e	2.58a	2.12c	2.00d	2.06d	0.64c	0.74a	0.55d	0.69b	0.70ab	0.71a
Lincoln, NE	363	2.27b	1.74d	2.60a	2.16b	1.98c	1.87cd	0.63d	0.72ab	0.53e	0.66c	0.69b	0.71a
NE mean	1 452	2.27b	1.77e	2.51a	2.10c	1.98d	2.00a	0.64d	0.72a	0.55e	0.67c	0.69b	0.68b
Pendleton, OR	321	2.56b	2.23c	2.05d	2.38b	2.45b	2.85a	0.66c	0.68b	0.71a	0.68b	0.66cb	0.59d
Pendleton, OR	339	2.43b	2.12c	1.99c	2.36b	2.33b	2.70a	0.67c	0.68ba	0.71a	0.68bc	0.66bc	0.58d
Pendleton, OR	352	2.64b	2.23cd	2.09d	2.53b	2.41cb	2.87a	0.69c	0.71b	0.74a	0.69c	0.69cb	0.60d
Pendleton, OR	354	2.43b	2.08dc	1.95d	2.38ba	2.24bc	2.51a	0.68c	0.70b	0.73a	0.67c	0.69b	0.62d
Pendleton, OR	355	2.89b	2.53c	2.22d	2.70b	2.69cb	3.14a	0.68c	0.71b	0.74a	0.69cb	0.69cb	0.62d
Pendleton, OR	349	2.73b	2.38c	2.15d	2.66b	2.52cb	2.90a	0.71c	0.72b	0.75a	0.70c	0.71cb	0.64d
OR mean	2 070	2.61cb	2.26d	2.07e	2.50b	2.44c	2.83a	0.68d	0.70b	0.73a	0.68c	0.68c	0.61e
Kutztown, PA	357	2.04b	1.80dc	1.92c	1.80d	1.94c	2.30a	0.69c	0.72b	0.67c	0.74a	0.69cb	0.62d
Kutztown, PA	358	2.04b	1.87c	1.89c	1.77d	2.01cb	2.48a	0.70c	0.71b	0.70cb	0.76a	0.69cb	0.58d
PA mean	715	2.04b	1.83d	1.90dc	1.78e	1.98c	2.39a	0.69d	0.71b	0.69cd	0.75a	0.69cb	0.60e
W. Lafayette, IN	90	2.22a	1.66cb	2.29a	1.60c	1.70cb	1.90b	0.66c	0.79a	0.62c	0.80a	0.77a	0.70b
Florence, SC	363	1.98b	1.77c	2.23a	1.88c	1.86c	1.88c	0.74b	0.77a	0.68c	0.77a	0.75a	0.74a
Florence, SC	363	1.94b	1.75c	2.15a	1.79c	1.82c	1.96b	0.73c	0.76a	0.68d	0.77a	0.75ba	0.73b
Florence, SC	353	2.08b	1.83c	2.31a	1.93c	1.93c	2.06b	0.73c	0.77a	0.67d	0.77a	0.75ba	0.73b
Florence, SC	348	1.96b	1.92b	1.85c	1.77d	2.01b	2.29a	0.69c	0.70c	0.72b	0.76a	0.70cb	0.63d
Florence, SC	351	2.14b	2.21b	2.02c	1.86d	2.29b	2.54a	0.76c	0.75c	0.78b	0.82a	0.73c	0.69d
Florence, SC	347	2.03cb	2.09cb	2.00c	1.86d	2.22b	2.50a	0.73b	0.72b	0.74b	0.78a	0.71b	0.65c
Florence, SC	306	2.31c	2.43cb	2.16d	2.00e	2.58b	2.83a	0.73c	0.70c	0.75b	0.79a	0.69c	0.64d
Florence, SC	334	2.79c	2.47cb	2.19d	2.07e	2.59b	2.84a	0.74c	0.71c	0.76b	0.80a	0.70c	0.66d
Florence, SC	349	2.42c	2.58cb	2.22d	2.17e	2.73b	2.96a	0.69c	0.66c	0.73b	0.76a	0.65c	0.60d
Florence, SC	349	2.34c	2.59b	2.19d	2.15d	2.72b	2.90a	0.72b	0.68c	0.75a	0.77a	0.68c	0.63d
SC mean	3 463	2.20cb	2.16c	2.13c	1.95d	2.27b	2.48a	0.73c	0.72b	0.72b	0.78a	0.71b	0.67d
Grand mean	10 847	2.52b	2.18e	2.40c	2.25d	2.29d	2.62a	0.70d	0.74b	0.69c	0.74a	0.73b	0.67d

† RMSE and r^2 are reported here, but means separation was conducted on transformed values. See text for a discussion and equations.
‡ Model identifiers as in Table 2.
§ Within rows, means for either RMSE or r^2 followed by the same letter are not significantly different by the Waller–Duncan test at $\alpha = 0.05$.
¶ Highlighted values indicate the numerical minimum for RMSE and numerical maximum for r^2.

came from the two Idaho sites. Judging from values of RMSE, TFIT was the numerically superior method in 12 site-years, of which 7 were at Florence, SC. In 7 of the 12 site-years, the numerical edge was also significantly better, at the 0.05 level, than the next-best method. Significance of results for r^2 was essentially the same, with TFIT being numerically superior in 15 site-years, and 8 of those significant at the 0.05 level. Consistency of the performance is reflected by significance of the grand mean of r^2 for TFIT.

Two important points can be seen in Table 4. First, although the TFIT model performed numerically better than the other methods for 15 site-years, it did not at Pendleton, Lincoln, the 2 Idaho sites, and 5 of the Arizona sites. As these site-years represent a significant portion of the total test, the reasons for these results bear further study. Second, the reason for relatively poorer performance at those sites appears to be different. The 6 Arizona sites have the 6 highest r^2 values, whereas the 2 yr for Idaho, the 4 yr for Lincoln, and the 6 yr for Pendleton have the 12 lowest. The r^2 values for TFIT in Arizona are actually higher than those for TFIT at sites where TFIT was the best performer. Clearly, performance of TFIT did not diminish in Arizona. Rather, the performance of the other methods was considerably improved there. On the other hand, performances of the TEMP model, the best performer at Pendleton, and of SAWTOOTH, the best performer at Lincoln, were about the same as they were for the other sites. Clearly, TFIT and the other models were not able to match daily air temperature patterns as well in these two as in other sites. All models performed poorly for the Idaho sites.

Generality of TFIT Parameters

The first indication of generality is how different the normal curve is for different sites. Figure 1 shows the mean normalized air temperature pattern for all years in the eight states represented. The values for different sites in Arizona were essentially the same. The only noticeable difference between the two Idaho sites was that the Reynolds Mountain site contributed the jog in the nighttime pattern. The curves for seven of the eight states are not materially different, although one could

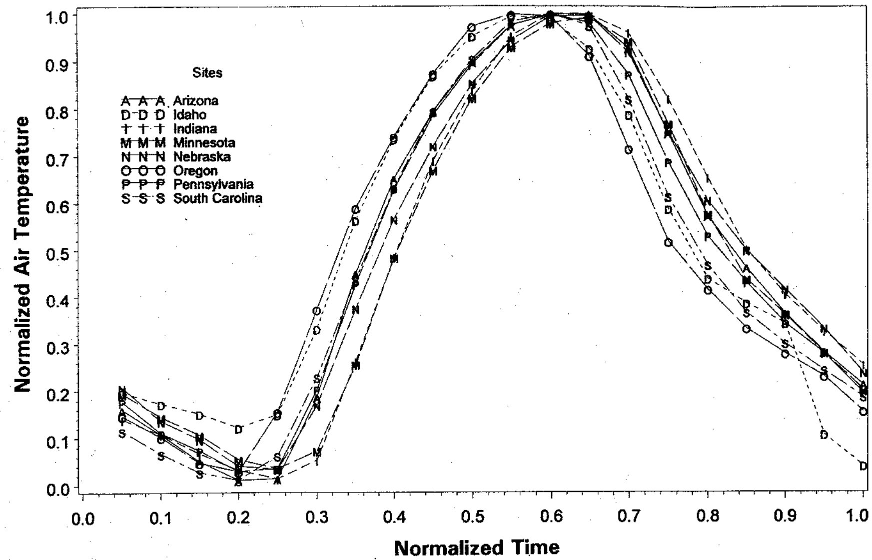

Fig. 1. Comparison of normalized air temperature plotted as a function of normalized time for all sites. Individual values are the means for all years at each site. Arizona sites and Idaho sites are averaged across sites and years.

argue that the curve for Oregon is shifted somewhat earlier than the others. The curve for Idaho is qualitatively different from the others, with the day's low often occurring before midnight.

The generality of TFIT was also evaluated by using the calibration parameters from the 1985 South Carolina data set and testing that against all other site-years. The results are shown in Table 5. The salient finding in this exercise is that the use of South Carolina's parameters does not decrease the annual mean r^2 very much. In the cases of the Idaho and Pendleton sites, r^2 improved enough to make TFIT superior to the other five methods. This surprising result is partially explained by the existence of many atypical diurnal patterns in those data sets. Inspection of individual days showed common occurrences of short-term (≈2–3 h) spikes and drops on the order of 5°C. There were also many days for which the times of the maximum or minimum were not typical. For such a data set, use of the median at a given time may not be as suitable as the use of a pattern from a more uniform site (for example, one of the Arizona sites). Where the distribution of temperatures at a given time is broadened (or bimodal), a median temperature may fall between the typical and anomalous temperatures, thus fitting neither. Then, the apparent paradox of another site's parameters fitting better is plausible.

SUMMARY AND CONCLUSIONS

In about half the cases, the TFIT model performed better or as well as the best of five other methods to model the diurnal air temperature pattern. At the Arizona sites where other models performed better, TFIT r^2 values were still >0.80. Poor performance at Pendleton and the two Idaho sites using on-site calibration data was improved by substituting South Carolina parameters, suggesting that a more extensive prescreening method (here, only days with rain were excluded from calibration data sets) to eliminate anomalous patterns would significantly improve the performance of the model for the more typical days.

The explicit normalization both of air temperature and of time reduced annual variation in the diurnal pattern, improving generality and the ability to transfer among sites. Normalizing time requires the time of sunrise and sunset, which can be obtained using tables or algorithms. Implementation of the TFIT model is not appreciably more difficult than using the simplest method, SAWTOOTH, and is much easier than the other methods.

Table 5. Values of RMSE and r^2, for local calibrations described in the text, and for the SC85 (South Carolina 1985) calibration normals.

		r^2		RMSE	
Location	**Year**	**vs. self**	**vs. SC85**	**vs. self**	**vs. SC85**
Morris, MN	**1988**	**0.81**	**0.75**	**2.12**	**2.64**
Aguila, AZ	**1988**	**0.83**	**0.86**	**2.38**	**2.28**
Coolidge, AZ	**1988**	**0.84**	**0.84**	**2.39**	**2.45**
Parker, AZ	**1988**	**0.84**	**0.84**	**2.23**	**2.24**
Safford, AZ	**1988**	**0.87**	**0.87**	**2.31**	**2.26**
Tucson, AZ	**1988**	**0.85**	**0.85**	**2.24**	**2.29**
Yuma Valley, AZ	**1988**	**0.82**	**0.84**	**2.34**	**2.33**
AZ mean		**0.84**	**0.85**	**2.31**	**2.31**
Boise, ID (Quonset)	**1993**	**0.59**	**0.65**	**4.30**	**4.14**
Reynolds Mtn., ID	**1993**	**0.47**	**0.55**	**3.65**	**3.50**
Lincoln, NE	**1992**	**0.68**	**0.67**	**2.10**	**2.21**
Lincoln, NE	**1993**	**0.65**	**0.64**	**2.02**	**2.13**
Lincoln, NE	**1994**	**0.69**	**0.68**	**2.12**	**2.27**
Lincoln, NE	**1995**	**0.66**	**0.65**	**2.16**	**2.28**
NE mean		**0.67**	**0.66**	**2.10**	**2.22**
Pendleton, OR	**1983**	**0.68**	**0.74**	**2.38**	**2.08**
Pendleton, OR	**1984**	**0.68**	**0.75**	**2.36**	**2.02**
Pendleton, OR	**1985**	**0.69**	**0.76**	**2.53**	**2.11**
Pendleton, OR	**1986**	**0.67**	**0.76**	**2.38**	**1.90**
Pendleton, OR	**1987**	**0.69**	**0.77**	**2.70**	**2.22**
Pendleton, OR	**1988**	**0.70**	**0.78**	**2.66**	**2.13**
OR mean		**0.68**	**0.76**	**2.50**	**2.08**
Kutztown, PA	**1986**	**0.74**	**0.74**	**1.80**	**1.84**
Kutztown, PA	**1988**	**0.76**	**0.76**	**1.77**	**1.82**
PA mean		**0.75**	**0.75**	**1.78**	**1.83**
W. Lafayette, IN	**1979**	**0.80**	**0.74**	**1.60**	**1.94**
Grand mean		**0.73**	**0.75**	**2.39**	**2.32**

Perhaps the most attractive feature of the TFIT model, beyond the performance obtained by allowing the weather site to define its own pattern, is the foundation it provides for the next generation of stochastic air temperature generators. The parameters of the beta distribution can be used, for example, in Markov chain models that preserve autocorrelation of the temperature series in the presence of anomalous events, which themselves can be impressed on the series with historically accurate frequency.

ACKNOWLEDGMENTS

The authors thank the cooperators who supplied the hourly temperature data used: Kim Kroll, Don Reicosky, Marvin Schreiber, Ken Hubbard, Ron Rickman, Paul Brown, and Greg Johnson.

REFERENCES

Acock, B., V.R. Reddy, F.D. Whisler, D.N. Baker, J.M. McKinion, H.F. Hodges, and K.J. Boote. 1983. Response of vegetation to carbon dioxide 002. The soybean crop simulator GLYCIM: Model documentation 1982. Joint program of the USDOE Carbon Dioxide Res. Div. and the USDA-ARS, conducted at the USDA-ARS Crop Simulation Unit and Dep. of Agronomy, Miss. Agric. & For. Exp. Stn. USDA-ARS, Mississippi State, MS.

Campbell, G.S. 1977. An introduction to environmental biophysics. Springer-Verlag, New York.

De Wit, C.T., J. Goudriaan, and H.H. van Laar. 1978. Simulation, respiration and transpiration of crops. Pudoc, Wageningen, The Netherlands.

Fernandez, C.J. 1992. Simulation of normal annual and diurnal temperature oscillations in non-mountainous mainland United States. Agron. J. 84:244–251.

Floyd, R.B., and R.D. Braddock. 1984. A simple method for fitting average diurnal temperature curves. Agric. For. Meteorol. 32: 107–119.

Goudriaan, J., and P.E. Waggoner. 1972. Simulating both aerial microclimate and soil temperature from observations above the foliar canopy. Neth. J. Agric. Sci. 20:104–124.

Haan, C.E. 1977. Statistical methods in hydrology. Iowa State Univ. Press, Ames.

Johnson, M.E., and E.A. Fitzpatrick. 1977. The monthly mean diurnal temperature curve. Arch. Meteorol. Geophys. Bioklimatol. Ser. B. 25:265–274.

Jones, C.A., and J.R. Kiniry. 1986. CERES–Maize: A simulation model of maize growth and development. Texas A&M Univ. Press, College Station.

Kline, D.E., J.F. Reid, and F.E. Woeste. 1982. Computer simulation of hourly dry-bulb temperatures. Va. Agric. Exp. Stn. No. 82-5. Virginia Polytech. Inst. & State Univ., Blacksburg.

Lemon, E., D.W. Stewart, and R.W. Shawcroft. 1971. The sun's work in a cornfield. Science (Washington, DC) 174:371–378

Myrup, L.O. 1969. A numerical model of the urban heat island. J. Appl. Meteorol. 8:908–918.

Parton, W.J., and J.A. Logan. 1981. A model for diurnal variation in soil and air temperature. Agric. Meteorol. 23:205–216.

Reicosky, D.C., L.J. Winkelman, J.M. Baker, and D.G. Baker. 1989. Accuracy of hourly air temperatures calculated from daily minima and maxima. Agric. For. Meteorol. 46:193–209.

Richardson, C.W., and D.A. Wright. 1984. WGEN: A model for generating daily weather variables. ARS-8. USDA-ARS, Beltsville, MD.

Sanders, C.G. 1975. Comments on the model for estimating the completion of rest for "Red Haven" and "Elberta" peach trees. Hortic. Sci. 10:560–561.

SAS Institute. 1990. SAS/STAT user's guide. Version 6. Vol. 1. SAS Inst., Cary, NC.

Steel, R.G.D., and J.H. Torrie. 1980. Principles and procedures of statistics: A biometrical approach. 2nd ed. McGraw-Hill, New York.

Walter, A. 1967. Notes on the utilization of records from third order climatological stations for agricultural purposes. Agric. Meteorol. 4:137–143.

Wilkerson, G.G., J.W. Jones, K.J. Boote, K.T. Ingram, and J.W. Mishoe. 1983. Modeling soybean growth for crop management. Trans. ASAE 26:63–73.

Worner, S.P. 1988. Evaluation of diurnal temperature models and thermal summation in New Zealand. J. Econ. Entomol. 81(1):9–13.